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PAPER

From Doubt to Drive: How Instructional Modality and Self-Efficacy Shape Motivation in Remedial Spatial Visualization Courses

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ABSTRACT

Spatial thinking is the foundation for successful problem-solving and critical thinking. Scholars have confirmed that spatial skills are essential tools for problem solving in fields such as engineering, design, physics, and mathematics. Drawing on Bandura's self-efficacy theory, this study investigates the impact of instructional modality, self-efficacy, and attitudes toward a spatial visualization app on student motivation in the context of an engineering remedial spatial visualization course. Our study focused on undergraduate engineering students from two cohorts with different instructional modalities, one in 2019 and the other in 2020. This study employs a quantitative approach, gathering data through questionnaires to measure student motivation, self-efficacy, attitudes toward the app, computer-aided design (CAD) experience, gender, and instructional modality. Our findings indicate that instructional modality significantly influenced student motivation, with online instruction during the pandemic being associated with lower motivation. Furthermore, significant predictors of student motivation were identified as self-efficacy and attitudes towards the app, independent of instructional modality. The findings provide insights into strategies for educators to implement educational technology in their courses while also remaining committed to nurturing student self-efficacy in online and in-person learning.

KEYWORDS

spatial training, remedial courses, self-efficacy, student motivation, instructional modality

1 INTRODUCTION

In the report "*Learning to Think Spatially*," the National Research Council states that spatial thinking is "a major blind spot in the American educational system." According to the report, spatial thinking is the foundation for successful problem-solving and critical thinking [1]. Scholars have confirmed that spatial skills are

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essential tools for problem-solving in fields such as engineering, design, physics, and mathematics [2–4].

Moreover, researchers assert that spatial skills are a fundamental predictor of success in STEM disciplines [4–6]. An 11-year longitudinal study of high school students concluded that spatial ability is critical for shaping educational and occupational outcomes. According to the study, spatial reasoning skills were strong indicators for the selection of STEM-related high school courses, college majors, occupations, bachelor's, and graduate degrees. Lastly, the study notes that historically, talent searches focused on identifying students with high mathematical and verbal reasoning skills. However, this approach has inadvertently overlooked a substantial reservoir of untapped talent [7].

The literature provides substantial evidence supporting the significant role of spatial skills in fostering success within STEM fields. This contribution is underscored by their connection with mathematics, improved performance in first- and second-year STEM courses, and their role in facilitating understanding of fundamental concepts within the engineering curriculum [8–10]. Mix and Cheng delve deeper into the connection between spatial representations and mathematical skills, claiming that spatial representations are integral to mathematical thought. These representations include both symbolic and mental representations. While symbolic representations include the ability to interpret graphs and diagrams, mental representations involve the coordination between verbal and written number systems [9].

The relationship between spatial skills and mathematical thinking becomes more apparent in the context of calculus, a course that often serves as a gateway to STEM majors. Calculus places significant emphasis on interpreting visual representations [10]. Proficiency in calculus requires the ability to extract information from diagrams, articulate concepts in mathematical language, and understand the rules and conventions associated with mathematical graphics [8], [11]. For example, rotating regions under the area of a curve requires an understanding of Cartesian and polar coordinate systems and the ability to translate them into mathematical symbols. These tasks require reasoning with visual representations, which underscores the significance of spatial visualization skills [8].

Spatial skills have a positive impact on foundational STEM courses such as chemistry, organic chemistry, physics, and statics [12–16]. In chemistry, students are required to visualize 3D molecular structures from 2D sketches, comprehend molecular behavior, and predict interactions in 3D space. A study by Carlisle et al. introduced three spatial interventions within the experimental section of the course. Their results revealed that student performance improved in identifying symmetry planes, visualizing in 3D, mentally rotating molecules, and translating spatial information [17]. Organic chemistry further emphasizes the importance of students with high spatial scores performing better on questions requiring problem-solving skills and mental manipulation of 2D representations of molecules [12].

In the field of physics, spatial representations in the form of graphs, diagrams, or physical models play a crucial role. Kozhevnikov et al. demonstrated a strong correlation between visual-spatial abilities and spatial competence in solving physics problems. Students with strong spatial skills are more likely to consider and apply motion parameters, interpret kinematic graphs, and effectively convert spatial problems into a different coordinated representation [13]. Another study demonstrated the impact of spatial training, revealing that students who underwent such training achieved higher scores in introductory physics compared to the control group [14]. Lastly, statics, an introductory course built on the foundation of mathematics and physics, also requires strong abstract thinking and spatial abilities [15]. A recent study by Davishahl et al. argued that spatial abilities form the foundation for learning experiences, driving representational competence in statics. The interpretation of representations and their effective application in problem-solving are critical for developing conceptual and procedural knowledge. Overall, the findings from Davishahl et al.'s study underscore the impact of spatial abilities on students' conceptual knowledge development in statics [16].

While spatial skills are crucial for success in STEM fields, there are significant variations among student populations. A substantial body of research suggests a gender gap exists, with males historically outperforming females in spatial abilities [4], [18], and [19]. Since spatial skills are crucial in various STEM fields, the absence of these skills in STEM students can result in lower retention rates, especially among underrepresented groups such as women [4]. Over the last two decades, literature has supported the effectiveness of spatial skill training for STEM students with lower spatial abilities [15], [18], and [20]. Many STEM schools have implemented proactive measures to address this challenge, such as offering structured training programs. A widely embraced approach employed by many schools involves specialized remedial courses tailored to assist students with low spatial skills to develop and enhance their ability to mentally transform 3D objects into 2D representations [21].

Furthermore, studies have revealed that students often have low self-efficacy and lack motivation towards remedial courses [22], [23]. This reluctance is often attributed to the additional time required on top of major coursework as well as the stigma associated with remedial courses. These perceptions could be enhanced if remedial courses were engaging and perceived as valuable. Bairaktarova et al. have demonstrated that technology-based teaching methods are as effective as traditional approaches in enhancing spatial visualization skills, possibly due to the increased motivation of students when using such media [21].

Building upon the 2019 study, the present study further investigates the impact of the spatial visualization app on self-efficacy in different learning environments (remote versus in-person instruction). Specifically, the study aims to address the following hypotheses:

- H0-1: There are no significant differences between males and females in their perceptions of spatial and sketching skills before and after taking the course.
- H0-2: There are no significant relationships between student motivation and the study's variables.
- H0-3: There are no moderating effects of the study's variables on the relationship between instructional modality and student motivation.

2 THEORETICAL FRAMEWORK

According to Bandura's self-efficacy theory, people's motivation and actions are influenced by personal beliefs rather than objective reality [24], [25]. As a result, people's actions are driven by their belief in accomplishment; otherwise, they have little incentive to act [24], [26]. Bandura defines perceived self-efficacy as one's belief in their ability to organize and execute actions to achieve specific goals [24].

The most significant source for boosting self-efficacy is through mastery experiences that help overcome failures and challenges. Developing perseverance and a strong sense of self-efficacy requires effectively navigating obstacles. Therefore, providing opportunities for individuals to master tasks is essential for building a strong foundation and increasing self-efficacy [24], [26].

In the context of this study, we utilize a spatial visualization app to enhance students' self-efficacy by offering a platform for mastery. This approach is particularly important in the context of remedial courses, as they often prolong the time needed to obtain a degree and increase the likelihood of non-completion [27], [28]. Since students entering remedial courses typically have low self-efficacy beliefs and perceive themselves as failures due to their placement in coursework, dropout rates may increase [22], [23]. These perceptions could be enhanced by making remedial courses engaging and valuable. Bairaktarova et al. have demonstrated that technology, through an engaging app, can be as effective as traditional teaching methods in enhancing spatial visualization skills, possibly due to increased student motivation [21]. An engaging and enjoyable app can help students develop self-efficacy and, ultimately, perseverance.

Verbal persuasion also plays a central role in self-efficacy. When individuals receive verbal encouragement, they are more likely to believe in their ability to achieve specific goals [26]. Therefore, faculty and peer encouragement can significantly influence students' beliefs about their ability to master a task. In this study, we aim to investigate students' self-efficacy in various learning environments using an online questionnaire. The questionnaire includes items on self-efficacy and student motivation, enabling us to investigate the influence of instructional modality.

3 METHODS

3.1 Participants and study setting

This study takes place in an engineering spatial visualization course. To assess students' spatial visualization abilities, the Purdue Rotation Visualization Test (PRVT: R), a test with demonstrated internal consistency and reliability, was administered [29], [30]. Students who scored 18 or below on this test were recommended to enroll in the spatial visualization course.

The target population for this research comprises undergraduate students enrolled in engineering programs. Following the approval of the Institutional Review Board (IRB), two cohorts of undergraduate students enrolled in engineering courses were invited to participate in the study. The study's sample came from the same engineering course but from different semesters. In total, 409 undergraduate students agreed to participate in the study and completed the questionnaire. This sample includes 203 students from the 2019 cohort and 206 students from the 2020 cohort.

For spatial training, both the 2019 and 2020 cohorts used a spatial visualization app developed by eGrove Education. This app, known as Spatial Vis, offers students the opportunity to practice freehand sketching, a crucial skill in developing and mastering spatial visualization skills. The app includes exercises involving isometric and orthographic views, with automatic grading of sketches. Additionally, students benefit from unlimited attempts to complete assignments, access hints, and view solutions [25]. Previous studies have demonstrated the effectiveness of the app through in-class activities and homework assignments [25], [31].

3.2 Measures

Undergraduate students' responses were collected using an online questionnaire that took approximately ten minutes to complete. Each questionnaire started with a reflection section, encouraging students to express what they had learned in the course and how they planned to apply it in future courses. Participants were assured of the confidentiality of their responses and were informed that their participation was entirely voluntary.

Student motivation was assessed using a set of 5 items, including statements such as "I enjoy doing spatial reasoning activities very much" and "Spatial reasoning activities are fun to do." Participants were required to rate their agreement with these statements on a 5-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). The reliability of this variable, assessed using Cronbach's alpha, demonstrated an excellent level of consistency (0.95).

Student self-efficacy was measured using eight items, such as "I think I am pretty good at spatial reasoning activities" and "I am satisfied with my performance in spatial reasoning activities." The scale for this variable was derived by calculating the mean scores of eight items. Participants were asked to express their agreement on a 5-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). The reliability of this variable was found to be significant (0.88).

Student attitudes toward using the app were assessed using six items, such as "Using the app helped me develop my skill in mental rotation." To ensure consistency, items with varying scales were transformed into a common one. Subsequently, the scores from all 6 items were averaged, resulting in a final common scale ranging from 0 (indicating an unfavorable attitude) to 4 (indicating favorable attitudes). The reliability of this variable, as assessed through Cronbach's alpha, fell within an acceptable range (0.85).

3.3 Limitations

During this study, specific limitations were taken into account. Firstly, the inclusion of the 2020 cohort, which experienced the global pandemic, may have introduced external factors that could have affected students' self-efficacy. This poses a threat to external validity, specifically concerning the interaction of setting and treatment [32]. We acknowledge that these external factors may influence the study's results and ecological validity, which refers to the generalizability of the findings to different settings [33].

Given that our study examines remote learning environments as one of the instructional modalities, the pandemic learning environment might not be generalizable to remote learning settings. Nevertheless, we believe this study provides valuable insights into how a pandemic may have affected students' self-efficacy.

Secondly, there is a potential threat to internal validity due to participant attrition [32]. Given the external stressors imposed by the pandemic, some participants may have chosen to drop out of the study or course. However, the study's robust sample size helps mitigate the risk.

Lastly, the nature of convenience sampling could introduce selection bias, as the participants enrolling in the recommended course might exhibit higher self-efficacy compared to those who chose not to participate [34]. To address this potential bias, two cohorts were included in the study: 2019 and 2020.

3.4 Data analysis

Statistical analyses were conducted to assess questionnaire measures and address our research questions. To evaluate item consistency and internal structure, we conducted a reliability analysis. Our research questions were addressed through several statistical tests. Firstly, we employed t-tests to identify significant mean score differences in sketching skills and spatial skills between males and females within each cohort. Secondly, multiple linear regression analysis was used to investigate the relationship between the study's predictors, which included instructional modality, computer-aided design (CAD) experience, gender, student self-efficacy, attitudes toward app usage, and the outcome variable of student motivation. Lastly, moderated regression analysis was utilized to assess whether instructional modality moderated the relationships between CAD experience, gender, student self-efficacy, attitudes toward app usage, and the outcome variable student motivation. The moderation effect was examined by testing the significance of the interaction term, followed by simple slope analysis to further assess the conditional effect of the predictors.

4 RESULTS

This section begins with descriptive statistics and intercorrelations among the variables. Secondly, the gender-based differences in perceptions of spatial and sketching skills are discussed. Finally, multiple linear regression and moderation regression analyses are presented.

4.1 Descriptive statistics

In Table 1, the descriptive statistics and intercorrelations are presented for modality, gender, CAD, student motivation, self-efficacy, and student attitudes toward using the app. Undergraduate engineering students reported a high level of motivation (M = 3.9, SD = 0.79) and self-efficacy (M = 4.024, SD = 0.55), with moderately positive attitudes toward using the app (M = 3.09, SD = 0.73). The correlations revealed several significant relationships, indicating that students' attitudes toward using the app were positively associated with instructional modality (r = 0.18), student motivation (r = 0.42), and student self-efficacy (r = 0.46). Additionally, student self-efficacy showed a positive relationship with CAD experience (r = 0.11) and student motivation (r = 0.65).

Table 1. Summary of descriptive statistics, reliability, and intercorrelations

Variables	*N*	*M*	*SD*	*Min*	*Max*	α^a	(1)	(2)	(3)	(4)	(5)	(6)
1. Modality	409	.504	0.501	0	1	–	–					
2. Gender	408	.373	0.484	0	1	–	0.017	–				
3. CAD	409	.337	0.473	0	1	–	–0.005	–0.015	–			
4. Motivation	409	3.9	0.792	1	5	0.95	–0.039	–0.020	0.052	–		
5. Self efficacy	409	4.024	0.545	1.875	5	0.88	0.020	–0.073	0.109*	0.645*	–	
6. Attitudes (App)	409	3.092	0.732	.389	4	0.85	0.183*	0.013	–0.061	0.421*	0.463*	–

Note: [a]Cronbach's alpha reliability. ***p < .01, **p < .05, *p < .1.

4.2 Gender differences in spatial and sketching skills

To assess the influence of gender on student perceptions of spatial and sketching skills, a t-test was conducted. In the 2019 cohort, as shown in Table 2, significant mean differences were observed between male (*M* = 2.643) and female (*M* = 2.23) participants in their pre-course perceptions of spatial skills, while no significant differences were observed in their perceptions of sketching skills. Furthermore, the table demonstrates significant mean differences between male (*M* = 3.977) and female (*M* = 3.757) perceptions of spatial skills *after* completing the course. However, there were no statistically significant differences in perceptions of sketching skills. In the 2020 cohort, as shown in Table 3, no significant differences in means were observed between male and female participants.

Table 2. Results of two-sample t-tests conducted on the 2019 cohort to compare student perceptions of spatial and sketching skills before and after taking the Spatial Visualization course, categorized by gender

Variables	*Male (n)*	*Female (n)*	*Male (M)*	*Female (M)*	*Difference*	*SE*	*t Value*	*p Value*
Spatial skills (before)	129	74	2.643	2.23	.414	.127	3.25	.002
Spatial skills (after)	128	74	3.977	3.757	.22	.103	2.15	.033
Sketching skills (before)	128	73	2.594	2.863	–.27	.156	–1.7	.086
Sketching skills (after)	129	74	3.892	3.973	–.082	.108	–.75	.452

Finally, in the 2020 cohort as shown in Table 3, no significant differences were found between male and female perceptions for either skill.

Table 3. Two-sample t-tests conducted on the 2020 cohort to analyze student perceptions of spatial and sketching skills, categorized by gender, before and after taking the Spatial Visualization course

Variables	*Male (n)*	*Female (n)*	*Male (M)*	*Female (M)*	*Difference*	*SE*	*t Value*	*p Value*
Spatial skills (before)	127	78	2.543	2.372	.172	.104	1.65	.1
Spatial skills (after)	126	78	4.127	4.038	.088	.091	.95	.333
Sketching skills (before)	125	78	2.704	2.859	–.155	.143	–1.1	.278
Sketching skills (after)	126	78	3.913	4.013	–.1	.114	–.9	.378

4.3 Regression analysis

Table 4 presents the results obtained from the multiple linear regression analysis, which examines the relationships between different predictors and student motivation. This analysis utilizes a multiple linear regression model to investigate the influence of each predictor on student motivation while controlling for the effects of other predictors. Overall, the regression model proves to be significant in predicting student motivation with an F-statistic of $F(5.402) = 63.80$, with $p < 0.01$. This model explains approximately 44% of the variance in student motivation, as indicated by the coefficients of $R^2 = 0.44$ and adj $R^2 = 0.44$. The omnibus F-test further confirms the significance of at least one predictor in relation to student motivation.

Specifically, the regression outcomes revealed several noteworthy findings. Instructional modality emerged as a significant predictor of student motivation ($B = –0.13$, $p < 0.05$), suggesting that the mean student motivation score for the online cohort was lower than that of the in-person cohort (difference = –0.13). Gender, on the other hand, did not show a statistically significant association with student motivation (B = 0.03, p > 0.05), suggesting that there was no significant difference in mean motivation scores between males and females (diff = 0.03). Similarly, CAD experience did not significantly relate to student motivation (B = 0.03, p > 0.05), indicating that students with or without CAD experience exhibit similar mean scores for student motivation (diff = 0.00).

Furthermore, the regression model highlights the significant role of student self-efficacy in predicting student motivation (B = 0.83, p < 0.05). Specifically, a one-unit increase in student self-efficacy corresponds to an expected increase of 0.83 in student motivation. Lastly, student attitudes toward using the app also showed a significant relationship with student motivation (B = 0.19, p < 0.05). In other words, each one-unit increase in student attitudes toward using the app is associated with an expected increase of 0.19 in student motivation.

Table 4. Regression analysis to evaluates the influence of instructional modality, gender, CAD experience, student self-efficacy, and student attitudes toward using the app on student motivation

Variables	*b*	*SE*	*t-Value*	*p-Value*	*[95% Conf. Interval]*		*Sig*
Modality (2020)	–.132	.06	–2.18	.03	–.25	–.013	**
Female	.034	.061	0.56	.574	–.086	.155	
CAD	.002	.063	0.03	.978	–.123	.126	
Self-efficacy	.827	.062	13.28	0	.705	.949	***
Attitudes (app)	.187	.047	4.00	0	.095	.279	***
N	408						
F-test	63.799						
p-value	0.000						
R-squared	0.442						

Note: ***p < .01, **p < .05, *p < .1.

4.4 Moderation analysis

Table 5 presents the results of a moderation analysis conducted to investigate whether instructional modality moderated the relationship between student motivation and other variables in the model. In this nonadditive model, which allows both intercepts and slopes to vary as a function of predictors in the model, the overall model was found to be significant in predicting student motivation (F (9.398) = 35.97, p < 0.01, R^2 = 0.45, adj R^2 = 0.44). The coefficient of multiple determination (R^2) indicates that, as a whole, while accounting for the variation in self-efficacy as a function of other predictors, the model explained approximately 45% of the variance in student motivation. However, the model parameters revealed no significant interaction between instructional modality and any variable in the model when predicting student motivation. This result implies that regardless of instructional modality, student self-efficacy consistently has a significant effect on student motivation. In other words, the relationship between student motivation and student self-efficacy remains consistent across different instructional modalities.

Table 5. Moderation analysis investigating the moderating impact of instructional modality on the correlation between student motivation, self-efficacy, gender, CAD experience, and attitudes toward using the app

Variables	*b*	*SE*	*t-Value*	*p-Value*	*[95% Conf. Interval]*		*Sig*
Modality (2020)	–.942	.456	–2.07	.039	–1.838	–.046	**
Female	.013	.088	0.15	.883	–.159	.185	
CAD	–.053	.089	–0.60	.552	–.229	.123	
Self-efficacy	.777	.081	9.60	0	.618	.936	***
Attitudes (App)	.145	.061	2.39	.017	.026	.265	**
Modality (2020) × Female	.035	.123	0.29	.776	–.206	.276	
Modality (2020) × CAD	.102	.127	0.80	.421	–.147	.351	
Modality (2020) × Self-efficacy	.114	.127	0.90	.369	–.135	.364	
Modality (2020) × Attitudes (app)	.097	.095	1.02	.308	–.09	.285	
N	408						
F-test	35.967						
p-value	0.000						
R-squared	0.449						

5 DISCUSSION

Past studies have supported a gender gap in spatial visualization abilities, with males generally outperforming females [35]. Further, previous research also indicates that students with strong spatial skills are more likely to succeed in engineering [19], [36]. However, this study revealed an interesting trend: significant differences were observed in the 2019 cohort, indicating that male students had higher perceptions of spatial skills before taking the course, but no differences were observed in the 2020 cohort between male and female students. Voyer et al. point to socio-cultural reasons for differences in spatial visualization skills [35]. These findings may suggest evolving trends in gender-related disparities in spatial abilities. For example, studies have shown that cognitive sex differences have narrowed considerably over the past few decades in spatial abilities [37] and mathematics [38–40], likely due to improved educational access and reduced gender bias [41].

Numerous studies have explored interventions aimed at enhancing spatial visualization skills, with a particular focus on female students. For instance, Sorby and Baartmans (2000) developed a course that enhanced the spatial skills of male and female engineering students, with the most significant improvements noted among female participants [42]. A meta-analysis by Uttal et al. revealed the effectiveness of spatial skills training in improving spatial visualization for male and female students, with more significant improvements observed in female students [43]. In addition to these broader trends, both classes in this study were taught by a female instructor. This may further support female students' self-efficacy, interest, and performance in STEM courses, aligning with the significance of faculty behavior and verbal encouragement in supporting self-efficacy development [26], [44].

Additionally, it is important to consider that while the app was used in both classes, the 2020 class was conducted virtually due to the COVID-19 pandemic lockdown. This may have also contributed to the differences between the 2019 and 2020 data. Students encountered numerous challenges during this time, including technical issues, difficulties in maintaining a work-life balance, and a lack of motivation [45]. Moreover, the virtual format limited faculty interactions, which likely played a significant role in making teaching modality a significant predictor of student motivation. Specifically, students who received online instruction during the COVID-19 pandemic exhibited lower motivation levels in this study, as supported by the literature on student experiences during this time [46]–[48].

This study identified several key predictors of student motivation, including teaching modality, self-efficacy, and attitudes toward the app. Prior research emphasizes the crucial role of both self-efficacy and motivation in enhancing spatial visualization skills through educational interventions [36], [49], and [50]. The relationship between student motivation and student self-efficacy remained consistent across different instructional modalities, further illustrating the importance of self-efficacy. Moreover, students' attitudes towards using the app showed a significant association with student motivation, even when controlling for other predictors in the model.

This study supports the importance of cultivating student motivation by fostering self-efficacy. Student self-efficacy was also positively correlated with prior CAD experience and student motivation. Typically, students have low self-efficacy and a lack of motivation toward remedial courses [22], [23]. However, leveraging educational technologies, such as apps, can effectively transform these courses into engaging and meaningful experiences. Such technologies provide students with opportunities to further develop their self-efficacy by gaining mastery [24], [26]. The efficacy of educational technologies, as demonstrated by Bairaktarova et al., aligns with the findings of this study, highlighting the significant impact of attitudes toward the app and self-efficacy on student motivation [21].

6 CONCLUSION

This study aimed to address three hypotheses regarding the development of spatial skills. Null hypothesis 1 posited that there are no significant differences in male and female students' perceptions of spatial and sketching skills before and after taking the remedial course. Our analysis found no gender differences in perceptions after completing the course. However, prior to the course in 2019, there were gender differences in perceived spatial and sketching skills, but this was not observed for the 2020 class.

Null hypothesis 2 posited that there is no significant relationship between student motivation and the study's variables. Our findings reject the null hypothesis, revealing significant relationships between student motivation and the study's variables, specifically self-efficacy, attitude towards the app, and teaching modality.

Finally, null hypothesis 3 suggested that there were no moderate effects of the study's variables on the relationship between instructional modality and student motivation. Our analysis confirmed the null hypothesis, revealing no significant interaction between instructional modality and any variable in predicting student motivation. This result implies that regardless of the instructional modality, student self-efficacy has a significant effect on student motivation.

Considering these findings, we recommend that educators not only embrace the use of educational technology in their courses but also remain committed to nurturing student self-efficacy and motivation in both physical and virtual classrooms. The significance of these factors persists even in remote teaching environments. Despite these promising results, our study is not without limitations. Further research in this area could involve qualitative interviews to delve into understanding student experiences, post-pandemic replication of the study, longitudinal investigations, or the inclusion of additional data sources such as CAD skills assessments, app performance metrics, or final course grades.

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